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A DISCRETE EVENT SIMULATION MODEL FOR RELIABILITY MODELING OF A CHEMICAL PLANT

Bikram Sharda
Scott J. Bury

Engineering and Process Sciences, Core R&D
2301 N. Brazosport Blvd.
The Dow Chemical Company
Freeport, TX 77541, USA

ABSTRACT

This paper discusses a discrete event simulation model developed to identify and understand the impact of different failures on the overall production capabilities in a chemical plant. The model will be used to understand key equipment components that contribute towards maximum production loss and to analyze the impact of a change policy on production losses. A change policy can be classified in terms of new equipment installation or increasing the stock level for the failure prone components. In this paper, we present the approach used and some preliminary results obtained from available data.

1 INTRODUCTION

Chemical plant operations typically consist of a large number of components with complex interactions and numerous failure modes. For plants that are running at a "sold-out" capacity, downtime means significant production and sales losses. To run the plant with minimum downtime, it is necessary to understand the critical components within the plant and implement new components, inventory control and preventive maintenance policies for the critical components.

This paper discusses a discrete event simulation model being developed to understand and identify key failure components for a chemical plant. The chemical plant considered here produces more than 15 different types of products, consists of ~40 different subsystems (such as reactors, wash tanks, refining system) and there are more than 250 different types of component failures (based on historical data), which occur in different subsystems. Based on historical data, 36% of the production losses were due to equipment failures. To maximize the plant production, a study is being carried out to identify critical subsystems and their individual components that contribute towards significant production loss. This study will also help in understanding the effect of change policies in terms of new component installation and inventory control policies for reduction in production loss. The DES modeling of this chemical plant operation presents challenges as it involves both continuous and discrete flow of material in the plant.

A barrier to successful execution of a study like this is scenario overload. To efficiently execute the key task of identifying the critical components, we designed a systematic approach. After model verification and validation, the simulation model will be first used to see a "base case" production against different products without any failures. This step will define the maximum attainable production for each product without failures. The model will then be run by considering failures for a particular subsystem (for instance, reactor system). After running the simulation model by considering failures in each subsystem, a Pareto analysis will be carried out to determine which subsystems are critical. Within each subsystem, the individual components will then be evaluated to identify components causing more frequent and costly downtimes. These components can then be analyzed for change policies such as implementing new designs or changing the inventory control policies. This systematic approach examines at the system hierarchy from the outside in, instead of an exhaustive search considering each failure. This reduces the number of possible simulation scenarios and generates data that are easier to understand and evaluate.

The paper is organized as follows. Section 2 provides a brief overview of the production process. Section 3 describes the DES simulation modeling approach, section 4 provides the preliminary results and section 5 presents the summary and future work for this project.

2 PROCESS OVERVIEW

The operations of the chemical plant being considered can be subdivided into following main steps. Note the combination of discrete (batch) and continuous processing steps.

1. Raw product loading (discrete)
2. Raw product mixing (discrete)
3. Reaction (discrete)
4. Intermediate storage 1 (discrete)
5. Raw product washing- (continuous)
6. Drying (continuous)
7. Blending (continuous)
8. Intermediate storage 2 (continuous)
9. Final Packaging (continuous to discrete)

The first two steps in the operation involve preparing the required type of raw products for reactor operation. After the raw material is prepared, it is sent to the reactors for production. There are currently N_1 number of reactors available for production, which operate in parallel. The reactor material is then sent to immediate storage, where the material waits for chemical removal and final drying operations. There are currently N_2 number of dryers operating in parallel for drying the product. After the drying operation, the material is sent to a blender and finally it is stored in storage bins for final packaging. There are currently N_3 number of parallel storage bins. In the final packaging, the finished product is packed in bags and sent for delivery.

The chemical plant produces only one type of product at a time. On changeover from one product to another, the new product is not allowed to go inside the washing system if there is previous product already available in the subsequent systems. So, the reactors can start producing the next product, but it cannot send this product to the storage (step 5). In case of a failure of a particular subsystem, the production output and input of that subsystem is stopped and resumed only when the repair is performed. It is assumed that intermediate products are not discarded in case of a failure.

3 DES MODEL FOR CHEMICALPLANT

In this section, we present the DES simulation model developed for the chemical plant and the approach used for critical component identification.

3.1 DES Simulation model

Figure 1 shows a snapshot of a part of the DES model developed for the chemical plant using ExtendSim® simulation software. The ExtendSim® simulation tool allows for hierarchical modeling that promotes a clean and organized model structure that enhances understanding by the non-model developers. The information required for running the simulation model was stored in the integrated databases in ExtendSim®. The input required for the running the simulation model can be classified in the following categories:

1. Simulation parameters: Simulation run length, number of replications.
2. Production information: Production schedule, reactor batch times, product produced per reactor batch, wash, dryer and other system flow rates.
3. Failure information: Time between failures distribution (TBF), time to repair distribution (TTR), initial stock level, reorder time distribution, reorder quantity, failures to consider.

Based on the production schedule, the number of reactor batches required is calculated and the flow rates of different subsystems are set. The failure information is grouped and stored according to different subsystems.

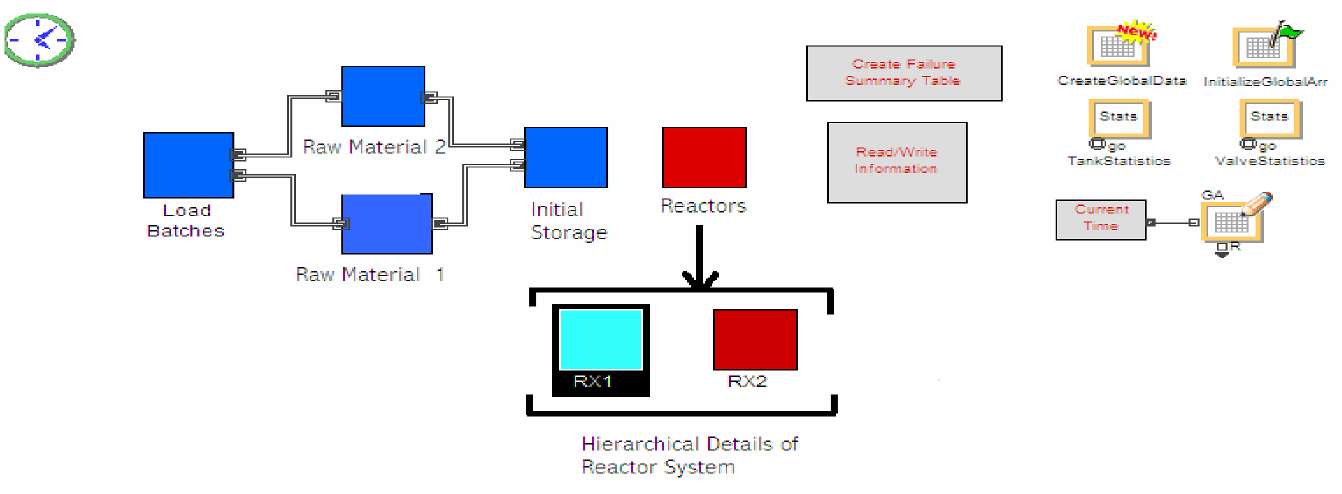

Figure 1: DES model for the chemical plant

For each failure component within a subsystem, failure information such as TBF, TTR, reorder time, reorder quantity is recorded. It is important to point here that subsystems such as wash, dryer system can have different flow rates depending upon the type of product being produced.

To simulate the effect of change of inventory control policies of failure-prone components such as re-order point, stock level and time to reorder, custom blocks were created. Figure 2 shows the stock replenishment algorithm. In the beginning of the simulation, the time between failures (TBF) of different components within a subsystem is initiated. When the TBF is reached, the blocks check for stock level of the component. If the component is available, the repair is performed and part is replaced. If the part is not available then there is a wait for the new part arrival and after the part arrives, a repair is performed. After the repair activity, the spare part stock is reduced. In case the new stock level is equal to reorder point, a new stock order is placed. Note, that in this model the reorder time is stochastic.

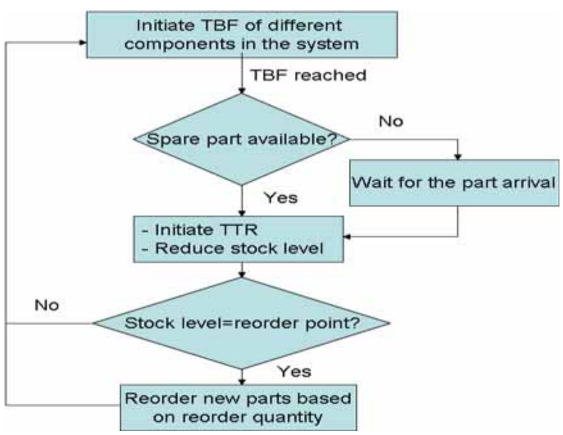

Figure 2: Stock replenishment algorithm

After completion of the simulation, the model stores following set of information in a database:

1. Failure summary: time between failures, time to repair, number of stock outs, number of re-order assigned.
2. Miscellaneous summary: daily production summary, reactor system production history, production history of subsystems such as wash system and dryer system.

Figure 3 shows a failure summary report generated by the simulation model. It lists information such as time between failures for each failure component within each subsystem. This information is used for further phases of the analysis. The miscellaneous summary reports are used to evaluate the actual production with/without failures and to see the affect of different failure types on each product type. In addition, this information is used for model verification and validation.

Record #	ArrivalTime	FailID	TTR	TBF	Reorder Time
1	12/12/2007 1:21:23	4	34.07	29.55	200.29
2	4/13/2008 7:57:22	29	28.98	118.33	205.82
3	8/12/2010 23:15:08	6	19.31	737.12	192.85
4	12/18/2011 13:29:02	30	32.96	1094.37	196.47
5	3/20/2012 7:36:14	3	57.58	1160.08	203.45
6	4/8/2012 9:14:08	21	22.70	1173.26	197.78
7	2/16/2013 1:37:23	21	19.76	227.53	207.67
8	7/17/2014 6:13:39	8	20.32	1775.59	199.21
9	7/11/2015 23:51:22	29	29.20	1918.00	209.94
10	3/27/2016 20:58:43	19	89.80	2222.62	198.07
11	6/16/2016 18:45:39	10	26.06	2280.67	201.06
12	4/3/2017 2:59:44	22	39.39	2490.63	208.78

Figure 3: Failure summary report

The variability in simulation model was mainly due to uncertainty in reactor production times and component failures. During the model verification phase, the model production/day for each product type was compared against historical production/day. Other model verification steps included, wash system and dryer system production/reactor batch, number of reactor batches/day.

3.2 Approach

To identify critical subsystems and components, the following systematic approach was used:

1. Run the simulation model without any failures and record base production/day for each product type.
2. Consider the failures for each subsystem and compute annual production loss.
3. Identify the subsystems causing highest production loss (A, B, C classification).
4. For the subsystems with highest production loss, find the critical components which contribute towards maximum downtime (A, B, C classification).
5. Evaluate the impact of change policies for critical components (Management action).

The production loss/day for each product type can be defined as:

Production loss/day=Base production-production considering losses.

In the present work, the last step involves end user interaction as they will define the possible scenarios to consider based upon the simulation results. The scenarios will be aimed at answering questions such as: How much downtime is reduced if the stock level of critical component is changed from X1 to X2? Once the possible scenarios are outlined, a further simulation study will be conducted to see, the effect of these scenarios.

4 PRELIMINARY RESULTS

In this section, we present some preliminary results generated for a product type whose information was available. For the preliminary analysis the effect of inventory control policies was ignored and was assumed that the stock outs do not occur.

Based on the historical data, 3 major subsystem components were used for preliminary analysis. Table 1 summarizes mean annual production loss, total annual failures and mean annual downtime hours associated with these 3 major subsystems. It must be pointed out here that these results are obtained considering only one product type, but when all the data is available, the analysis will be performed on a product mix. The results reveal that production loss due to subsystem C was significantly higher as compared to other 2 subsystems. Despite having a higher number of failures for subsystem B, the production loss was not significantly high.

Table 1: Production loss due to failures for different subsystems

Sub system	Mean annual production loss (lbs)	Total Failures	Mean annual downtime (hours)
A	66,709±11,441	8.60±0.9	27.64±3.
B	23,941±1,995	20±1.2	105.12±2
C	130,082±25,393	18±3.0	68±9

Figure 4-5 shows the time between failure (TBF) distribution of subsystem C and a Pareto front of components causing the failures of subsystem C. The Pareto analysis reveals that the failure components 3 and 4 contribute towards 35% of failures of subsystem C.

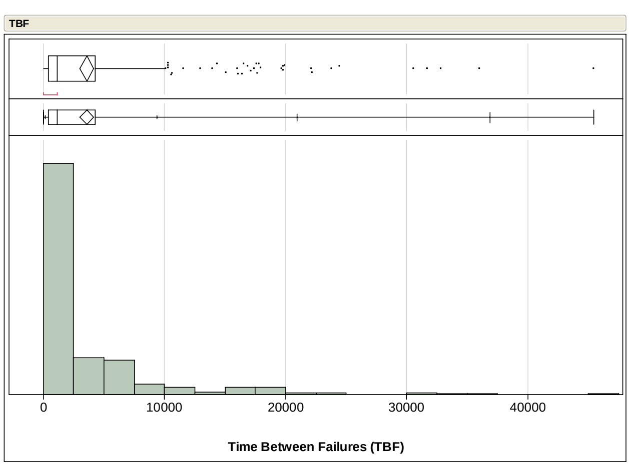

Figure 4: Time between Failure distribution for subsystem C

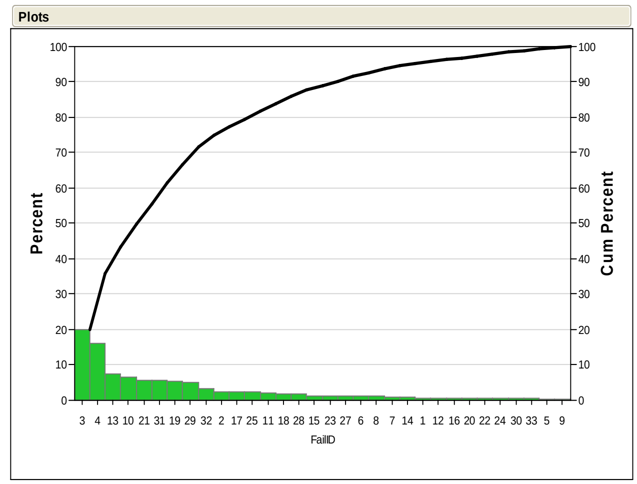

Figure 5: Pareto front of failure components within subsystem C

Such information will be provided to the end users for further analysis. The end users can define different scenarios to understand cost benefits associated with different actions such as effect of installing new critical components or changing the stock levels. Once the scenarios are outlined, a further simulation study will be conducted to see the effect of these changes.

5 SUMMARY AND FUTURE WORK

A discrete event simulation model was developed to identify and understand the impact of different component failures on the overall production capabilities in a chemical production plant. The model will be used to not only identify critical subsystems but also will be used to see the impact of a change policy on the overall production capabilities. Currently, we are in the process of gathering information required for full model validation.

Our preliminary results on available information provide some key insights into failure properties of different subsystems and impact of their failures on overall production. Once the critical components are identified, the next step will involve understanding the impact of change policies on the production capabilities. The present work shows the potential of discrete event simulation for such applications. The use of a systematic approach to investigate the system hierarchy from the outside in is an efficient method for complex models

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AUTHOR BIOGRAPHIES

BIKRAM SHARDA is a member of the Modeling group of The Dow Chemical Company's Engineering and Process Sciences organization in Core R&D. His research interests include simulation modeling, risk analysis, Bayesian statistics and pattern recognition techniques. He received his Ph.D. degree in Industrial Engineering from Texas A&M University. His email address is <brsharda@dow.com>.

SCOTT J. BURY is a Technical Leader in the Modeling group of The Dow Chemical Company's Engineering and Process Sciences organization in Core R&D. His research interests include process simulation of chemical processes using both continuous and discrete event technology. He is a certified Six Sigma Black Belt. He is a member of INFORMS. His email address is <scott.bury.sb@dow.com>.